Multi-objective simulation and optimisation of dairy sheep farms: Exploring trade-offs between economic and environmental outcomes

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Abstract

A decision support tool for sheep farming systems (PASTOR-DSS) was developed to investigate trade-offs between economic and environmental objectives on Spanish dairy sheep farms. The tool combines a hierarchical stochastic simulation model at three levels with a multi-objective optimisation procedure based on genetic algorithms. The first level of simulation includes rumen, reproduction and nutrient balance submodels. These three submodels are integrated into an animal model, which constitutes the second level. The third level is the farm, which includes the flock, the feeding and reproductive management, the availability of feeding resources, and the farm economics. The multi-objective genetic algorithm applies to the farm level. The tool was validated for the different levels of simulation, with outputs having an acceptable level of accuracy and representing correctly the links between feeding and reproduction. The tool was used to optimise the Latxa breed farming systems of the Basque Country (Spain). Two farm types were simulated: a COAST farm located in low-altitude Atlantic conditions and longer grazing period, and the INLAND farm located in mountain areas with a shorter grazing period. The optimisation provided a set of optimal solutions with different economic and environmental (N excretion) performances. The optimal solutions increased the financial margin over feed costs in both farms (+24% and +22% for COAST and INLAND, respectively). The final space of solutions showed a clear trade-off between the economic and environmental performance (nitrogen excretion). The difference in the financial margin over feed costs between the solutions could be interpreted as the opportunity cost of greening in policy design, i.e., the payment that farmers should receive to change their farming methods to reduce nitrogen pollution.

Highlights

- PASTOR-DSS combines bio-economic simulation and multi-objective optimisation in sheep dairy farms.
- Genetic algorithms allow optimising multiple objectives on complex farms.
- Trade-offs between economic and environmental performance are quantified.
- PASTOR-DSS is useful when discussing management alternatives with stakeholders and in policy design.

Keywords

bio-economic modelling, genetic algorithm, optimal solutions, trade-off analysis, Latxa breed

Abbreviations

GA: Genetic Algorithms

MOGA: Multi-objective GA

DSS: Decision support system

DMI: Dry matter intake

BCS: Body condition score

LW: Live weight

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1 Introduction

Livestock systems are complex due to multiple dynamic technical and economic interactions; therefore, they are difficult to optimise. For example, the economic evaluation of feeding and reproductive management options should consider the strong interactions between them; otherwise, it will fail to detect the best strategy in the medium-long term. Furthermore, when livestock use grazing resources, animal responses, as well as environmental (e.g., land use) and social (e.g., labour) components, must be evaluated (Ripoll-Bosch et al. 2012).

Models can simulate livestock farming systems, but if we want to evaluate the heterogeneity of animal response, the models should consider that livestock systems are composed of multiple groups of animals and that variability between individuals is large regarding biological traits and response to management. Hence, the simulation of variability using stochastic models is necessary when optimising certain variables (Mayer *et al.*, 1998).

When management strategies are modified, trade-offs between (and within) sustainability pillars (i.e., economy, environment and social) normally arise. Therefore, when modelling farming systems, we must cope not only with the complexity of the system and the representation of the individual variability but also with the existence of variables of different natures and dimensions and the trade-offs that can occur at different scales when we change the objectives of the modelling exercise.

Most livestock farming system models described in the bibliography are designed to run management strategies or to predict the system’s dynamics based on a set of parameters (see Goutennoire et al., 2011 for a review). However, if the models are intended for use as decision support tools, they also should include the capacity to find the best or optimal solution or range of solutions, for one or several technical, economic, environmental or social objectives (Bernués et al., 2011).

Linear programming is the most commonly used method for optimising whole-farm operations to examine the benefits of a new technology within the whole farm context (Goutennoire et al., 2011). However, linear programming has some limitations for coping with the complexity of livestock farming systems; relationships between variables are usually not linear, and the combined effect of the inputs and outputs is not additive (Alford, 2003). To address these problems, particularly those that relate to the non-linear relation between input variables and outputs, various authors have proposed alternative evolution algorithms —collectively termed ‘evolutionary algorithms’— to determine optimal solutions (see Mayer et al., 2005 for a review). Evolutionary algorithms encompass a range of different ‘nature-inspired’ methods, including genetic algorithms (GA).

Inspired by the concept of natural selection, the GA selects the best (i.e., higher fitness, or capacity for an organism to survive and transmit its genotype through reproduction to offspring compared to competing organisms) solutions and obtains new solutions from them. This process of evaluation of fitness, selection and generation of new solutions is repeated until a solution is found. Fitness evaluation in livestock farming optimisation should include different objectives. Multi-objective GA (MOGA) can operate either by assigning weights to the different objectives or by obtaining a set of optimal solutions that can be used to analyse trade-offs between the different objectives (i.e., economic and environmental).

Traditional features of dairy sheep farming systems in the Basque Country (Spain) relate to grazing management, transhumance to mountain pastures and on-farm cheese-making. Since the breeding scheme for the Latxa breed began in 1982, important efforts have been made to improve several aspects of the production systems (Ruiz et al. 2002), including animal health, nutrition (silage production and utilisation of more concentrates), and reproduction (artificial insemination). Main weaknesses detected by farmers and technicians include the high price of concentrates and low price perceived by outputs (lamb and raw milk), as well as certain issues related to the farm's structure (geographical location, utilised agricultural area, etc.). Alternatively, improving the utilisation of the resources available through agroforestry and landscape management, and better nutrient recycling practices were stated as opportunities to enhance the competitiveness of the Latxa breed production systems (Ruiz et al. 2010). However, the system is constrained by the seasonal breeding behaviour of the Latxa breed.

In this article, we describe a decision support tool (PASTOR-DSS) for sheep farming systems that combines bioeconomic simulation and optimisation procedures based on genetic algorithms. We apply the tool to simulate two contrasting systems of dairy sheep farms and analyse the trade-offs between economic and environmental objectives.

2 Materials and methods

The decision support tool consists of the integration of a stochastic animal model (section 2.1) into a farm model (section 2.2) and multicriteria optimisation of the resulting simulated farm using genetic algorithms (section 2.3).

The first level of modelling includes the rumen, reproduction and nutrient balance. The interaction between these three submodels constitutes the animal model, the second level of simulation. One or several sets of simulated animals form the flock. The third level of simulation is the farm, which includes the flock, the feeding and reproductive management regimes, and the farm economics. The farm is the level where the MOGA is applied. A scheme of the three modelling levels is presented in Figure 1.

2.1 Animal model

The animal model represents different levels of detail, from rumen to flock. The animal class is defined by three submodels that represent rumen, reproduction, and energy and protein balance. The flock class consists of the aggregation of different elements from the animal class.

2.1.1 Rumen submodel

The rumen submodel defines animal intake from the offered ration. Its structure relies mainly on the work of Illius and Gordon (1991). The Illius and Gordon model was only based on the physical restriction of intake at the rumen level as a function of the animal live weight and the chemical characteristics of the forage. This model was modified by Herrero (1997) to include the protein degradation in the rumen (Alderman and Cottrill, 1993) and protein digestion according to the Sniffen model (Sniffen et al., 1992). At this stage, the use of concentrate in the ration was included in the model. From the Herrero model, Silveira (2000) included a metabolic regulation of intake with rumen capacity variation as a function of the feeding level. The bovine model of Herrero was adapted to sheep, including two new modifications: first, a new regulation of intake based on the metabolic energy provided to the animal, related to its requirements for energy for its potential production (Hackman and Spain, 2009), and second, the possibility of including two forages in the ration, one as a fixed quantity and the second *ad libitum*.

The inputs of the rumen submodel are the quality and quantity of the feeds included in the ration, the live weight, and the diet metabolicity. The parameters that define the quality of feeds are based on crude protein (CP), neutral detergent fibre (NDF), in vitro degradation parameters (cellular content, cellular wall digestible and gas production rate), and CP fractions (soluble, degradable and non-degradable). The submodel evaluates the dry matter input and output from the rumen hourly, and provides as outputs the DM intake from each feed of the offered ration, and the metabolizable energy and protein provided by the diet to the animal, every 24 hours.

2.1.2 Energy and protein balance submodel

This submodel (see Supplementary Information 2) simulates the partitioning of the energy and protein provided by the diet (output from the Rumen submodel) between the different physiological functions. Maintenance, pregnancy, and lactation requirements are calculated based on the recommendations of the Agricultural and Food Research Council (1993). Depending on the energy and protein balance of the ewe, this model simulates daily the body reserves storage or mobilisation, the live weight variation, the daily milk production, and the lamb growth. The submodel also provides the daily difference between intake and requirements in terms of metabolizable nitrogen (N surplus) and metabolizable energy (E surplus). These two terms are related to environmental issues through nitrogen excretion and efficiency in the use of energy.

2.1.3 Reproduction submodel

For each day of simulation, the reproduction submodel (see Supplementary Information 2) evaluates the probability of the occurrence of events related to ewe reproduction (mating, pregnancy, abortion or lambing). To account for seasonal anoestrus, the first event evaluated is oestrus. Oestrus probability is a function of the breed features and the day of the year, and it is modelled according to Dzakuma and Harris (1989). This basal probability is modified as a function of the implementation of ram effect, utilisation of hormonal treatments to induce oestrus, and use of artificial insemination (AI). Heat probability is based on oestrus probability, and it is decreased if the ewe has had previous oestrus. The probability of conception when the ewe is in heat depends on the number of heats after the start of the mating season, the use of hormonal treatment and AI, the body condition score (BCS), and the pre-mating feeding. Probabilities obtained for each event were transformed into discrete variables (i.e., Oestrus? Yes/No) using random numbers from 0 to 1 (i.e., in the evaluation of whether an ewe will have oestrus, if random number is less than the probability assigned to this event then Oestrus=Yes).

The parameters that define the basal oestrus probability were estimated for the Latxa breed using data from the blood progesterone concentration (Beltrán de Heredia, *Personal Communication*). The parameters that modify basal oestrus, heat and conception were obtained from a meta-analysis of 20 bibliographic references (Díez-Unquera, 2013). In Figure 2, the reproduction submodel is presented with some of the parameters used to simulate the behaviour and management for the Latxa breed.

The inputs of the reproduction submodel are the breed (with its associated parameters), the ewe physiological state, the number of days from conception if pregnant, the days from lambing if lactating, the BCS, and the start and end dates of the mating season/s (that is, the dates when the rams enter or are removed from the flock). Each day, the model updates the physiological state of each individual animal.

2.2 Farm model

The farm model represents the reproduction and feeding management and calculates the financial margin over feed costs (from now on financial margin). The feeding management can be defined for individual batches according to the physiological state of the animals. The model can accommodate different feeding batches for maintenance (dry, non-pregnant), flushing (a period of variable length before mating defined by the user), pregnancy, prepartum (a period of variable length before lambing defined by the user), and lactation. The lactation period can be divided into three periods of variable length (defined by the user). For each batch, rations can be stimulated for different periods in the year.

The ration offered is defined for each feeding batch and period. The ration is able to accommodate three components: one forage and one concentrate with a fixed amount, and one forage offered *ad libitum*. At animal level, the rumen module predicts the actual daily intake of each component starting with the concentrate, then fixed forage and finally ad libitum forage, until the maximum intake is achieved. The *ad libitum* forage can be defined as a grazing resource. The availability of the grazing resource is a function of the surface available, the monthly productivity at the start of grazing, and the stocking rate.

The reproductive management is defined according to the initial and final dates of the mating periods and the proportion of ewes to receive artificial insemination. The model is able to simulate from one to five periods of mating yearly, i.e., from extensive conditions of one lambing season per year to intensive strategies (5 lambings in 3 years), as with the STAR accelerated lambing system (Lewis et al., 1996).

The flock class included in the farm model simulates a group of animal classes generated stochastically, i.e., some parameters of the animal classes (ewes) are obtained by sampling a normal distribution at random (with mean and standard deviation defined by the user). The parameters that define each ewe at start are the age, weight, BCS, potential milk peak, and day of year when the next reproductive effect will happen. The definition of the flock at the start of the simulation also includes the number of dry, pregnant and lactating ewes. Using this type of generation of the initial flock, the model can simulate the actual variability of the flocks, deriving this variability not only from the genetic differences between animals but also from the environmental variability generated by the management in batches.

The farm model is simulated daily, from a short time-span (less than1 year) to long-term scenarios (several years). The model provides simulated productive and reproductive results at the animal level (e.g., daily DMI, BCS, and milk yield), and therefore, the mean and variability of the farm outputs can be simulated.

The economic component calculates the farm financial margin as the margin obtained from production income minus feeding costs, which constitute more than 50% of total costs in sheep farms (RENGRATI, 2017). The prices of inputs (i.e., feeds) and outputs (meat, milk, and cheese) can vary every month. Finally, as an environmental indicator, the model includes the nitrogen and energy balance of the farm (surplus between metabolizable nitrogen (N) and energy consumed in the ration and metabolizable N and energy used, respectively).

2.3 Genetic algorithm for optimisation

The bioeconomic simulation model is integrated with a multi-objective genetic algorithm (MOGA) optimisation routine (Fonseca and Fleming, 1993), which provides widespread opportunities for the utilisation of the tool.

The MOGA searches for optimal solutions based on the mechanism of natural selection and evolution. By applying the mechanism of natural selection in solving a problem, each solution to this problem is considered as an individual to be or not selected. The best adapted *individuals* (i.e., those with higher fitness) have a greater chance to *reproduce*, and so, when *crossed* with other individuals in the population (solutions) will probably render good solutions to the problem. This process creates *offspring with individuals who* share the characteristics of each parent. New generations have, therefore, a higher proportion of better adapted individuals, and over the generations, the population of individuals who provide better solutions remain. The MOGA search intends to find the solution that minimises a vector of objectives, which means to maximise fitness. Solutions in the MOGA population are sorted and developed by using a non-dominated sorting GA (Deb et al., 2000).

The most relevant parameters of the MOGA are i) the crossover operator, requiring two individuals (solutions), which selects a cut point at random in its chromosomes (i.e., the set of variables that define each individual) and exchanges the strings generated obtaining two offspring solutions; ii) the selection operator, whereby an individual with a probability inverse to its fitness (f_i) is chosen, so this probability is f_i/f_t, with f_t being the sum of fitness of all the individuals in the population; and iii) the mutations, whereby changes occur at random in the value of variables that define the individual.

In our case, an individual (solution) is formed by a set of values for some variables of the bioeconomic simulation. All variables related to the feeding and reproductive strategies presented in Table 1 (considered as inputs for the farm model) can be modified by the MOGA procedure. The first group of individuals subjected to MOGA were obtained at random within the normal range of each variable. The “fitness” of each individual was obtained from the mean outputs of the bioeconomic simulation model after different complete runs under the conditions defined at the solution (individual) proposed. The fitness of each solution was defined according to three economic and environmental objectives: maximising the financial margin and minimising the nitrogen and energy surplus. Finally, two criteria are needed to stop the search of the optimal solution: maximum number of iterations and convergence (where the mean fitness value remains stable during some iterations).

Table 2 presents the values for the parameters for the MOGA configuration used in this study. Values for the number of repetitions and number of iterations were obtained after testing different combinations, reaching an acceptable compromise between the time of optimisation and convergence of fitness (Díez-Unquera, 2013).

2.4 Implementation

The model and the optimisation algorithm were developed using Java language and object-oriented software development approaches. An operative interface is available at http://daiasolutions.ddns.net/pastor/main.html

2.5 Model validation

The animal and farm models were validated using historical data from the experimental dairy sheep flock of NEIKER-Tecnalia in Arkaute, in the north of Spain, obtained for the years 2007 to 2012. The total agricultural land was 15 ha (10 ha of meadows and 5 ha of crops). The experimental flock had 150 ewes and 50 ewe lambs from the Latxa breed. Characteristics of the experimental flock on January 1st were as follows: 65 kg live weight (SD= 3 kg), 2.5 BCS (SD= 0.2), and 2.5 kg milk peak (SD= 0.2 kg). Reproduction management consisted of 100% AI in September (natural breeding season) and natural mating for no more than 5 cycles after AI. Three weeks before AI, all ewes were evaluated for BCS and classified into two different batches; ewes with BCS below 2.5 were flush fed for six weeks. After lambing, lactating ewes were fed with forage and concentrates. Animals were permanently kept indoors until the end of March, when they started grazing in nearby meadows. Indoor feed was reduced according to the increasing herbage availability and decreasing milk yield. In June, all the flock was dried off, and the ewes remained outdoors as long as possible until late autumn, approximately one month before the start of the next lambing season.

Each submodel of the animal model was validated separately. The simulated outputs for voluntary intake provided by the rumen submodel were compared with i) data from the experimental farm of NEIKER; ii) bibliographical data (Nsahlai and Apaloo, 2007), which included the information on feed quality that was needed to run the model (see section 2.1.1); and iii) outputs of existing validated models, such as INRA (Jarrige and Agabriel, 1988) and SRNS (Cannas et al., 2004).

The validation of the reproduction submodel was based on the assessment of the influence that the changes in the inputs under different scenarios had on the outputs and the proper functioning of the submodel. The results were discussed with a panel of technicians and researchers who assessed the inputs and outputs; a procedure described as ‘face validity’ by Sargent (2013).

For the farm model validation, the initial flock simulated was generated to mimic the NEIKER experimental farm flock with the same mean and standard deviations for live weight, BCS and milk peak. The values for the feeding and reproduction management of the simulated farm are described in Table 1. One *ad libitum* resource was defined: conserved forage or grazing meadows, depending of the month. This resource (Table 3) was available to complete a diet based on a fixed amount of forage (alfalfa silage) and concentrate (Table 3). The flock was simulated for a period of three years, and only data from the last year was retained for comparison with the actual data.

2.6 Simulated farms

The Latxa breed dairy sheep farms in the Basque Country base their reproductive management on the constraints imposed by the availability of grazing resources and the seasonal breeding behaviour of the local sheep. In this section, the model combining bioeconomic simulation and optimisation (hereafter, PASTOR-DSS) was used to evaluate the feeding management and date of mating in two simulated farms with different availability of grazing resources.

The simulated farm had 100 ewes with the same basic characteristics of the experimental flock previously defined during the farm model validation. Two types of farms were defined depending on the agroecological conditions. The COAST farm simulated systems of production were located in low-altitude Atlantic conditions, where the milder weather allows a longer period of vegetative growth of grass and therefore a longer grazing period. The INLAND farm simulated systems were located in a Mountain area with shorter grazing periods.

The quality of the *ad libitum* resources varied between months, and we assumed the same values for the two types of farms. The quality of these resources and of the other feeds used in the rations is for the experimental farm (Table 3). The forage offered in rations with a fixed amount was assumed to be purchased. Based on the official data from RENGRATI (2017), a fixed price for concentrate (0.22 €/kg), forage (0.16 €/kg), and milk (1 €/l), was used whereas lamb price varied according to real market conditions (4.5 €/kg carcass around December and 2.5 €/kg carcass in May).

COAST and INLAND farms differed in the length of the grazing period and the monthly productivity of the pasture. The COAST grazing season lasted from February (800 kg DM/ha) to November (800 kg DM/ha), with a maximum productivity of 1300 kg DM/ha in June (Ferrer et al., 1990). The INLAND grazing season lasted from April (800 kg DM/ha) to October (900 kg DM/ha), with a maximum productivity of 1200 kg DM/ha in July (Besga,1996). In both cases, livestock density was 25 sheep/ha.

The same initial flock generated at random has been used in both farm types in order to avoid differences in variability at the start that could affect the comparison of simulation outputs between scenarios and systems. Each farm type was simulated for a period of three years and only data of third year was retained for evaluation and optimisation. The simulation was repeated 20 times and the mean and standard deviation of the main outputs of the animal and farm models were analysed.

Financial margin, N and Energy surplus were the simulated outputs to optimise in order to analyse the trade-offs between economic and environmental objectives in both COAST and INLAND scenarios. The optimisation was performed using the MOGA and the configuration described in section 2.3.

3 Results and Discussion

In this section, we present the results of the model validation, the model application describing the main features of the simulation outputs before optimisation, the results of the optimisation, and finally the trade-offs.

3.1 Model validation

For experimental farm data, with a range of observed voluntary intake from 0.7 to 1.2 kg DM/day, the correlation between the simulated and observed values was very high

(>0.9). For bibliographical data, with low quality forages and a range of observed voluntary intake from 0.4 to 0.9 kg DM/day, the correlation was more than 0.7. The simulated voluntary intakes with a diet based on alfalfa in ewes of different weights and physiological states were similar to those obtained with INRA but lower than those obtained with SRNS. Our submodel is comparable to the reference models (INRA, SRNS) but is more flexible since its base was more mechanistic and should therefore better predict the intake of complex rations.

Data from the NEIKER experimental farm were also used to validate the outputs from the nutrient balance submodel. Initial BCS, LW, and day of lactation from four batches of lactating ewes, together with predicted metabolizable energy and protein intake derived from the rumen submodel, were the inputs for the balance submodel. Weekly simulated and observed LW, BCS and milk yield in a period of 21 to 43 days, depending on data available in each batch, were compared. In the case of LW, prediction errors were between 0% and 7%; for BCS, the range was broader, with errors between -5% and 12%. For milk production, the most extreme errors in the estimates were -18% and 14%. The correlation coefficient between the observed and simulated values in the three variables showed high values, between 0.90 and 0.98 (see Supplemental Information 1).

For the reproduction submodel, after evaluation, the panel of experts considered that the model correctly simulated the values obtained in real flocks for fertility and lambing dispersion. The model responses to changes in the type of mating (natural or artificial insemination), mating length, date of male entry, and nutritional status of the sheep were considered adequate, and therefore, we concluded that the submodel can represent a wide range of reproductive management practices and strategies.

For the farm model validation, the simulated lambing pattern represented well the actual one at the experimental farm. For both simulated and actual data, the lambing season started on the third week of January, and 80% of the lambings took place in the first month of the lambing season.

Figure 3 shows the simulated and observed mean values in five years for the main outputs of the model: BCS, live weight (LW), and milk yield. Estimated mean values and patterns of change for the three outputs were, in general, satisfactory. For BCS and LW, the model captured the effects on the recovery of body reserves, which starts in April when meadows had the highest productive potential and when milk yield and nutrient requirements decrease, and then, the BCS recovery in autumn was captured again. The model sufficiently simulated the effect of change in the diet after the ewes finished lactation in July. Concerning mean milk production, the simulated data agreed with the mean produced by the flock, with only a slight underestimation for the maximum level of production around the milk peak, happening for most ewes in February.

The farm model is concluded to predict outputs with an acceptable level of accuracy. Although some outputs could be slightly over or underestimated, the tool correctly represented the links between feeding and reproduction.

3.2 Model application

The basis for the stochastic simulation at the animal level is the intrinsic individual variation of each animal (weight, potential milk production), the variation generated by the random events (like oestrus expression, conception, abortion…), and the management at batch level. Figure 4 represents the predicted milk production and BCS over two years for 20 ewes. For milk production, the differences in animal potential were clearly simulated, showing reductions in milk production in ewes with late lambing when the ration changes occurred at the batch level (at approximately day 550 of simulation). In the case of BCS, the seasonal variation was simulated accurately, but the variation among the animals increased with the day of simulation.

The individual response to the feed offered explains, in part, the high variability at the end of the simulation compared with the initial variability in the simulated flock. Because we used actual data of animal variability as model inputs, we assumed that this variability was caused by animal differences. The animal model allocates energy and protein according to the requirements of maintenance, pregnancy, and lactation simulated for each individual ewe. However, the effect of batch management on animals with different physiological states (i.e., day of lactation) can also contribute to the variability in animal weights and BCS. Some models recently developed for dairy cows account for genetic and environmental effects to better simulate the level of acquisition and allocation of nutrients (Puillet et al. 2016).

The stochastic simulation also produced information about the variability in lambing distribution. Lambing distribution changed under the different scenarios (Figure 4) due to modifications in reproductive management (i.e., length of the mating season) but also due to feeding management because of the feeding-to-reproduction link included in the model. In a future model update, this pattern of lambing could be used to derive labour requirements (for instance, to guarantee lambing supervision, feeding, milking and on-farm cheese-making) to obtain a better assessment of the economic and social consequences of the solutions obtained.

3.3 Optimisation

The MOGA optimisation process implemented for the COAST and INLAND farms provided a set of final solutions that can be placed over the space defined by environmental and economic objectives. Nitrogen and energy surplus followed the same trend, so only the solution for financial margin and N surplus are presented in Figure 5. For the mean obtained from all the solutions that accomplish in some way the objectives (average solution), COAST farms obtained higher financial margin than INLAND farms (168 vs 163 €/ewe.year) but also higher N surplus (47 vs 43 g of N/ewe.day).

Two solutions for each type of farm were selected to summarise the optimisation results: the solution with the higher profitability, OPT(€), and the solution with lower N surplus, OPT(N). Table 4 presents the main management variables, the costs and incomes, and the environmental outcomes for COAST and INLAND farms under different solutions: base (non-optimised using the experimental farm values), OPT(€), and OPT(N). Concerning the reproductive management, the MOGA optimisation did not modify the start of the mating season for the INLAND farm, but it proposed an earlier start (20 days) for the COAST farms. In all cases, the algorithm maintained the use of AI. Nevertheless, the length of the mating season increased in all the optimal solutions (31 days to 99 days longer than the base). Under these conditions, most of the ewes in the optimal solutions were dried off a few days before the first mating day, the day planned for AI, and considering that the model simulates a 19-day period of recovery from the dry-off day to the first day available for reproduction, AI was not used in most ewes.

Concerning the economic objective, the model assumes that the use of grazing resources has no cost; this is the case in many communal pastures in Spanish mountains. However, labour costs should also be included in the model, or proposed solutions should be evaluated while accounting for this aspect. For the environmental objective, only N and energy surplus were included in this first approach, but other aspects, such as GHG emissions or the delivery of ecosystem services (e.g., landscape maintenance), could be included in the future.

The assumption of no costs for grazing resources could be considered as a consequence of agri-environmental programmes that promote management of low-intensity pasture systems (European Commission, 2005). This fact, combined with the marked seasonal breeding behaviour of the Latxa breed (Ruiz et al. 2010), determined that solutions for the optimal start of the mating season were very close to the base scenario. On the other hand, the length of the mating season was higher in all the optimal solutions (both economic and environmental). Once again, the extra labour costs that would imply a longer lambing season could affect some solutions.

Economic and environmental outputs varied among simulations (repetitions) within the type of farm and solution. Coefficient of variation was very low, from 0.6 to 1%, for financial margin and low, from 1 to 13%, for environmental outputs. Homogeneity in the results could be used as an indicator of consistency of the solution obtained. Homogeneity of animal performance and of economic outputs are parameters of great interest to assess potentially interesting management alternatives, particularly if the grazing resources vary in quantity and quality along the years as a result of climate change. Therefore, the simulated variability obtained within animals (see above) and within repetitions (farms) could be included in future optimisations as objectives to be minimised.

The OPT(€) solutions increased the financial margin in both type of farms (+24% and +22% for COAST and INLAND, respectively). Details of the diets for the different physiological state batches and the lengths of the feeding periods are presented in Figure 6. In both types of farms, OPT (€) reduced the forage inclusion, whereas the concentrate was generally increased, in most of the non-lactating batches. On the other hand, for the lactating batches, the amount of concentrate was reduced, and the length of the supply of diet for the first phase of lactation was also reduced in both the OPT(€) solutions. Overall, in these scenarios, the cost of forage and concentrate were reduced compared with the base scenario, maintaining the income from milk and increasing the incomes from lambs due to a lambing pattern optimised to profit from high seasonal prices (Table 4). For the COAST farm, the higher income obtained in the OPT(€) solutions implied a 13% increase in N surplus, when compared with the base scenario, whereas for the INLAND farm, the increase in income was obtained without modifying the environmental outputs.

The OPT(N) solutions reduced the N surplus in both types of farms (-48% and -58% for COAST and INLAND, respectively). Compared with the OPT(€) solutions, the environmentally oriented solutions reduced the concentrate use in all feeding batches (except the diet for pregnant ewes outdoor in the COAST farm) and clearly increased the forage use in the lactating batches of the COAST farm, whereas it reduced forage use in the INLAND farm. This feeding management, in combination with the abovementioned changes in mating and milking season lengths, led to higher forage cost but also to a slight reduction in concentrate costs. The management proposed by the OPT(N) solutions penalized milk production compared with the average of the OPT(€) solutions (-11% and -15% for COAST and INLAND farms, respectively).

The solutions that optimised the financial margin largely reduced the feeding costs while maintaining the milk production. Farmers tend to design diets that do not limit the potential of any animal, but in accordance with the results (with the exceptions mentioned above), with an adequate management of the lactation length and rations, room still exists to increase farm incomes in these systems.

Surprisingly, the environmental (minimum N surplus) optimisations resulted in an increase of the forage costs and in the length of the mating and milking season (especially in COAST farms). This can be due to the high level of protein of grazing resources in some months. The use of *ad libitum* feeding of these resources by ewes at the end of milking season will lead to a high N surplus. Kebreab et al. (2001) have described this effect, concluding that the N pollution might be reduced by growing grass with moderate fertiliser application and using maize-based energy supplements formulated to provide protein with low degradability. Considering that the feeds available for simulation and optimisation had high levels of protein, the optimal solution for reducing N surplus also included a penalisation in milk production. From the individual milk production curves, simulated for the COAST farm when the objective is economic, we observed that most animals achieved the maximum potential of milk production (although some will be overfed at some stage), whereas under the environmental objective, the milk production of some ewes was restricted to limit the N surplus.

The outputs of the MOGA constitute a good basis for discussions on alternatives with stakeholders. The space of solutions provided by PASTOR-DSS showed a trade-off between economic performance and environmental issues (i.e., N surplus). A similar trade-off was also reported in the dairy cattle model proposed by Groot et al. (2012), where a larger operating profit was associated with larger N losses. Farm manure is a major source of nitrate pollution (Lord et al. 2002), and in most EU countries, legislation has already been introduced to limit the amount of manure N that can be spread onto land. Hence, the difference in the financial margin between the OPT(€) and the OPT(N) solutions could be interpreted as the opportunity cost of greening in policy design, i.e., the payment that farmers should receive to change their management to reduce N pollution.

To our knowledge, PASTOR-DSS constitutes the first deterministic, stochastic and dynamic model that includes an evolutionary algorithm optimisation. Groot et al. (2012) presented the FarmDESIGN tool that coupled a bio-economical model that evaluates the productive, economic and environmental performance at the farm level, with a multi-objective optimisation. However, FarmDESIGN is a static model and does not account for individual animal variability. Other recent approaches used only simulation modelling, either without (Ashfield et al., 2013) or with (Bohan et al. 2016) stochastic components. The inclusion of stochastic components provides useful information for decision-making. The analysis of adaptability of farming systems should rely on the optimal solutions not only for the mean output but also the variability of this output. Nevertheless, the parametrisation of the stochastic variables is not easy and can have a large influence on model behaviour (Villalba et al., 2006). PASTOR-DSS is able to minimise variability as an objective, but robust input datasets should be constructed to obtain adequate simulated variability between animals. Nevertheless, the MOGA allowed enough flexibility to incorporate stochastic results, avoiding the restrictions of linear programming that impair its use in some livestock models (Bohan et al., 2016).

One of the purposes of the PASTOR-DSS was to serve as a tool for decision-making. Therefore, it was designed with a visual web-based interface (http://www.pastor.udl.cat/pastor/). Despite being designed to be flexible enough to represent a wide range of sheep farming systems, PASTOR-DSS has some issues that could impair its use by technicians and farmers. First, the number of parameters of the rumen submodel, and especially of the reproductive submodel, that should be adjusted to match the type of animal to be simulated is very large. Second, the time consumed for optimisation is also large. Simulation was relatively fast; a simulation run of 3 years for a flock of 100 ewes takes less than 3 seconds to produce all outputs (intel-i5 processor), but the optimisation with 20 repetitions per solution and the MOGA parameters described in section 2.3 take six hours on the same computer. Third, the translation of grazing and feeding management to the model is not easy. At the moment, the interface of the model allows different uses of resources, forages and concentrates for the different physiological batches, in different periods of the year.

4 Conclusions

PASTOR-DSS is a modelling tool that combines bioeconomic simulation and optimisation that can be used to simulate complex scenarios and the behaviour of sheep farms. This tool is stochastic in nature and able to represent the interactions between animal nutrition and reproduction, providing information on animal performance means and variability. The integration of the simulated animals into a whole-farm model allows for the evaluation of the effects of changes in management on the economic and environmental outputs, in short and long timeframes. The use of a multi-objective genetic algorithm allows for the optimisation of feeding and reproductive practices in complex livestock farms considering different objectives. For Latxa breed sheep dairy farms, the optimal solutions increased the financial margin in different types of farms, although future versions of PASTOR decision support tool should include labour costs and other environmental objectives. The space of solutions showed the trade-offs between the economic and environmental objectives (i.e., N surplus). This decision support system could be useful to discuss alternatives with stakeholders and for policy design purposes.

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Table 1. Variables from the bioeconomic model that could be modified by the optimization procedure (values presented are the starting values based in actual data from the experimental flock at Neiker)

Feeding management		Reproduction management	
Variable	Value	Variable	Value
Length feeding period 1 lactation (%)	50	Date start mating season	7-Sep
Length feeding period 2 lactation (%)	30	Date end mating season	21-Dec
Length feeding period 3 lactation (%)	20	Threshold of milk yield to dry ewes (kg/d)	0.18
Forage during milking (kg/d)	0.8	Use of artificial insemination, AI (Yes/No)	Yes
Fixed forage (kg/d)		% of AI	100
maintenance	0		
prepartum	0.3		
flushing	0.2		
pregnancy	0.3		
period 1 lactation	0.8		
period 2 lactation	0.4		
period 3 lactation	0		
Fixed concentrate (kg/d)			
maintenance	0		
prepartum	0.3		
flushing	0.3		
pregnancy	0.2		
period 1 lactation	0.8		
period 2 lactation	0.6		
period 3 lactation	0.2		
Days from lambing to dry off	150		
Days concentrate prepartum	60		
Days concentrate flushing	40		

Table 2. Configuration of the genetic algorithm used for the optimisation of the bioeconomic model.

Parameter	Value
Natality (number of offspring solutions per iteration)	4
Number of individuals (solutions)	120
Number of parents	2
Crossover probability	1
Mutation probability of a gene (variable)	0.05
Mutation probability of an individual	1
Repeated individuals	Yes
Iterations	1000
Repetitions (number of farms simulated per solution)	20

Table 3. Type and quality parameters of the feed resources available per month used as input of the rumen submodel.

Month	Resource	kg DM/ha[1]	% CP	%NDF	CelC	CWD	k
January	Silage	-	16.0	49.1	0.51	0.13	0.03
February	Silage	-	16.0	49.1	0.51	0.13	0.03
Mars	Silage	-	16.0	49.1	0.51	0.13	0.03
April	Meadow	800	20.6	47.5	0.52	0.26	0.06
May	Meadow	900	20.6	47.5	0.52	0.26	0.06
June	Meadow	900	18.7	43.0	0.57	0.25	0.06
July	Meadow	500	12.1	58.3	0.42	0.12	0.03
August	Meadow	500	12.1	58.3	0.42	0.12	0.03
September	Meadow	700	17.7	48.8	0.52	0.18	0.06
October	Meadow	900	18.7	43.0	0.57	0.25	0.06
November	Meadow	800	16.8	43.9	0.56	0.25	0.06
December	Silage	-	16.0	49.1	0.51	0.13	0.03
All year	Alfalfa	-	19.2	40.4	0.6	0.12	0.071
All year	Concentrate	-	20.8	22.4	0.78	0.13	0.08

CP: Crude protein; NDF: Neutral detergent fibre; CelC: Cellular content (g/g); CWD: Cellular wall digestible (g/g); k: gas production rate

[1]: For grazing resources

Table 4. Optimal management, economic and environmental outputs of COAST and INLAND farms under different scenarios. For outputs, mean and standard deviation (in brackets) were obtained from 20 repetitions.

	Base[1]		Optimised (€)		Optimised (N)	
	COAST	INLAND	COAST	INLAND	COAST	INLAND
Management						
Start of mating	7-Sep	7-Sep	18-Aug	7-Sep	18-Aug	7-Sep
Length of mating (d)	105	105	204	190	204	136
AI used	Yes	Yes	Yes	Yes	Yes	Yes
Length of milking season (d)	150	150	116	236	200	82
Costs (€)						
Forage	8220	8216	1836	3290	10051	11113
	(73)	(78)	(49)	(69)	(113)	(70)
Concentrate	6835	6867	3723	3449	2194	3327
	(137)	(152)	(24)	(11)	(188)	(41)
AI	1317	1311	112	122	113	197
	(20)	(24)	(20)	(22)	(20)	(29)
Incomes						
Milk	54773	54775	54449	54660	48340	46268
	(1229)	(1245)	(1074)	(914)	(1254)	(966)
Lambs	7654	7726	8531	8348	8325	7343
	(363)	(268)	(239)	(309)	(257)	(359)
Financial margin over feed costs	46057	46107	57308	56148	44308	38974
	(363)	(268)	(239)	(309)	(257)	(359)
Environmental issues						
Nitrogen excess in diet (g/animal.day)	58.3	57.3	66	57.3	29.8	23.9
	(1.4)	(2.3)	(0.9)	(2.7)	(1)	(3.1)
Energy excess in diet (J/animal.day)	2.2	2.31	2.45	2.19	1.17	0.96
	(0.03)	(0.04)	(0.02)	(0.05)	(0.02)	(0.06)

[1] based on feeding and reproductive management of experimental farm

Figure 1. Schema of main components of PASTOR-DSS (time scale; inputs; outputs)

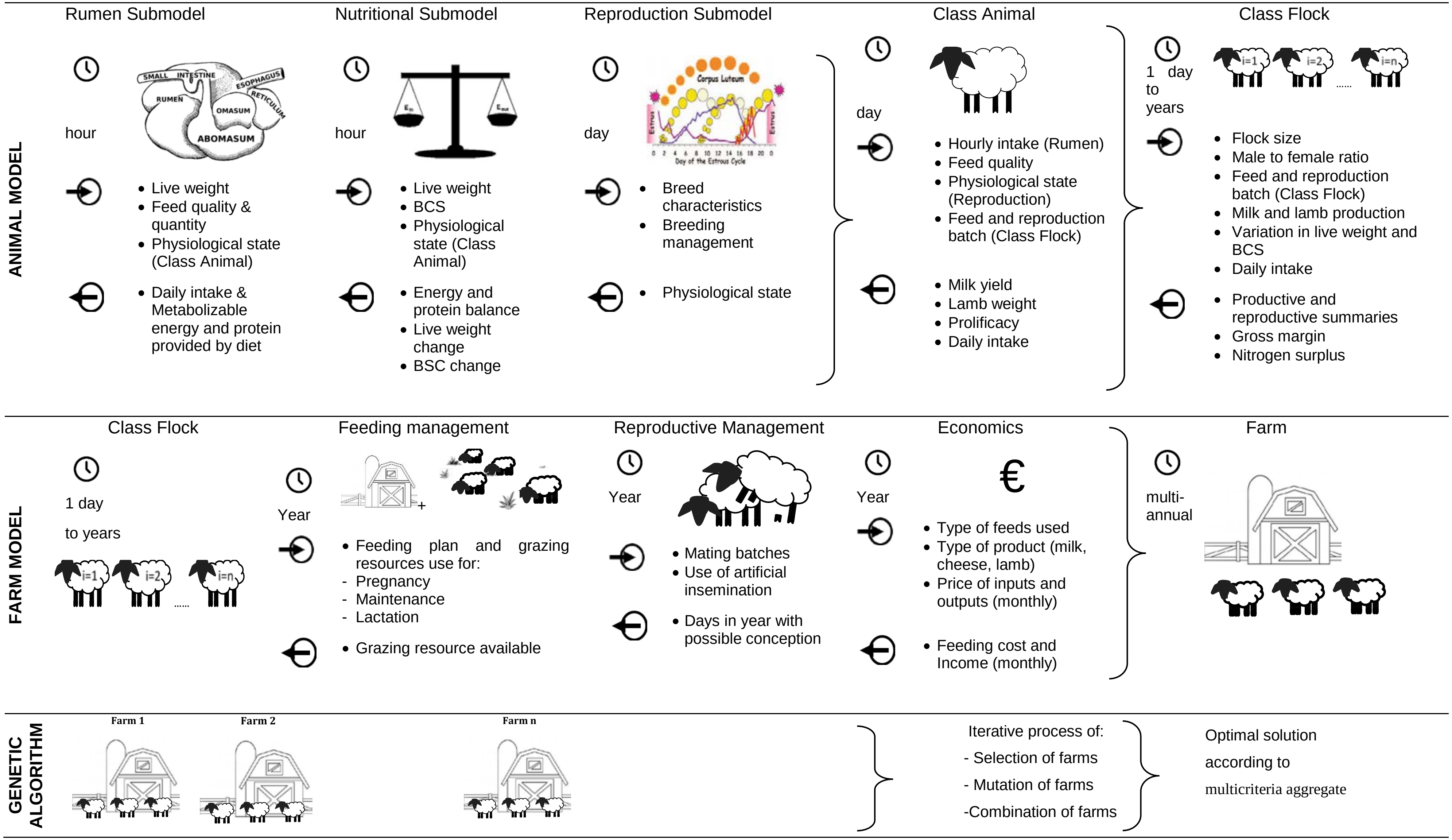


Figure 2. Diagram of the reproduction submodel with probability of conception (F) parameters estimated for the Latxa Breed.

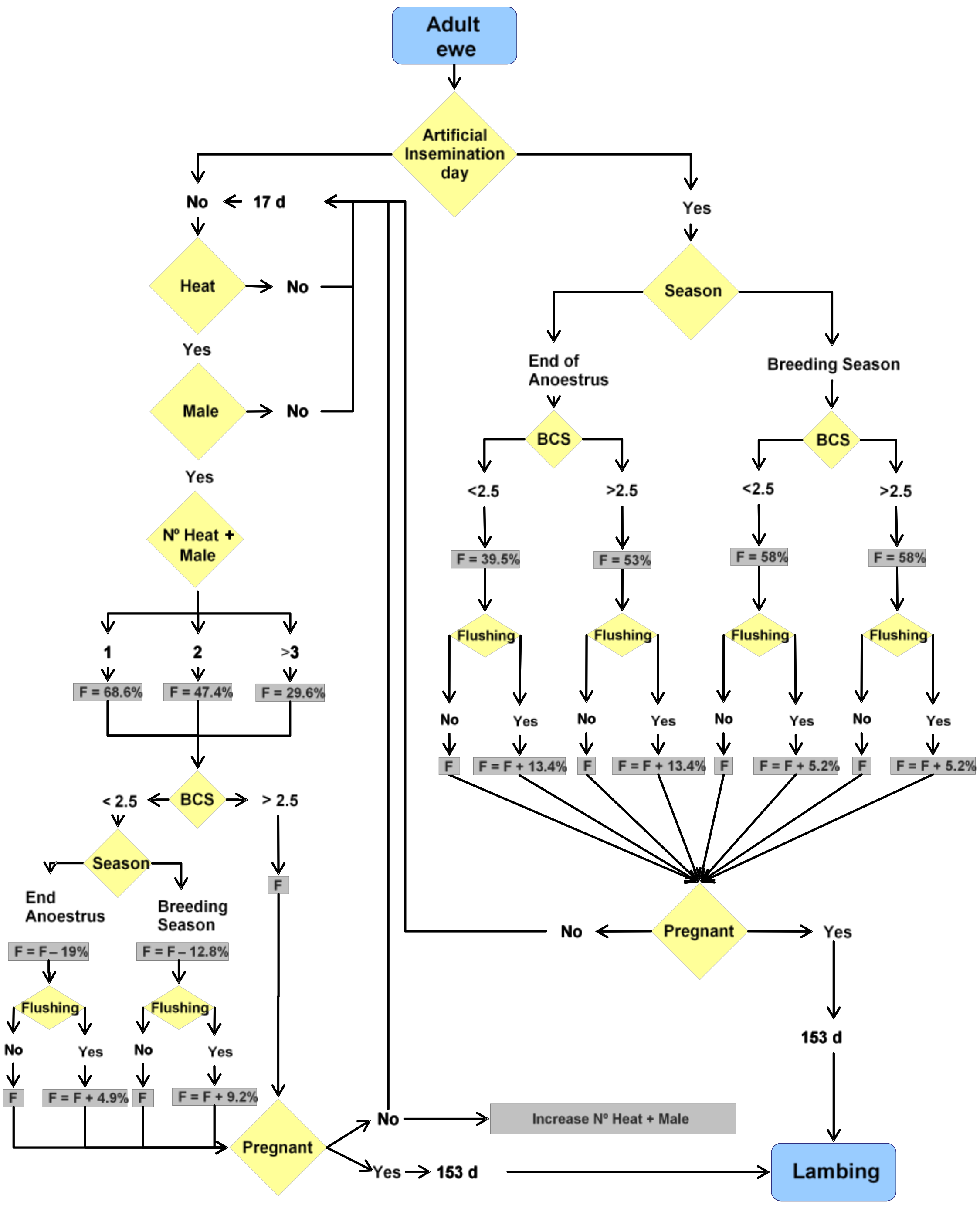


Figure 3. Live weight, BCS, and milk production, observed in the experimental farm and simulated by the bioeconomic model.

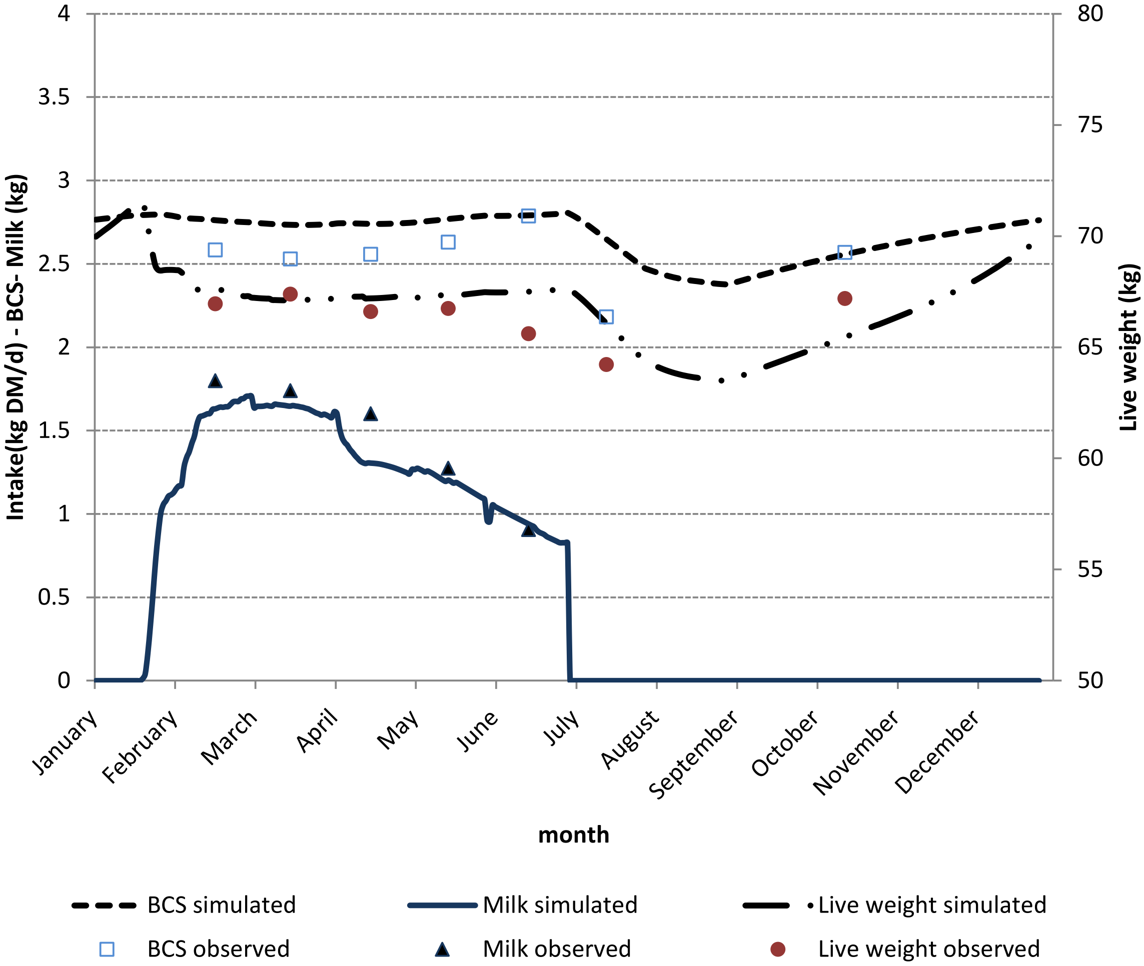
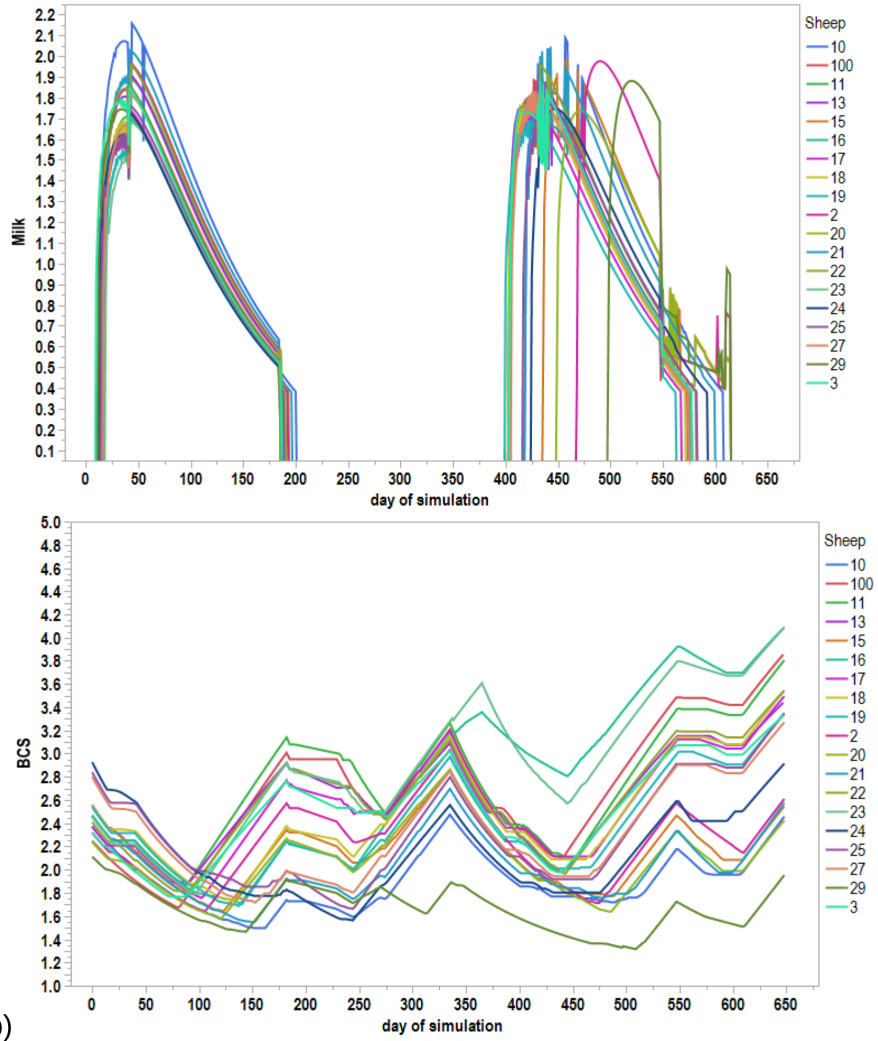


Figure 4. Simulated outputs obtained from the bioeconomic model. Milk and body conditions score (BCS) at sheep on a daily basis and lambing distribution of flock on a weekly basis



b)

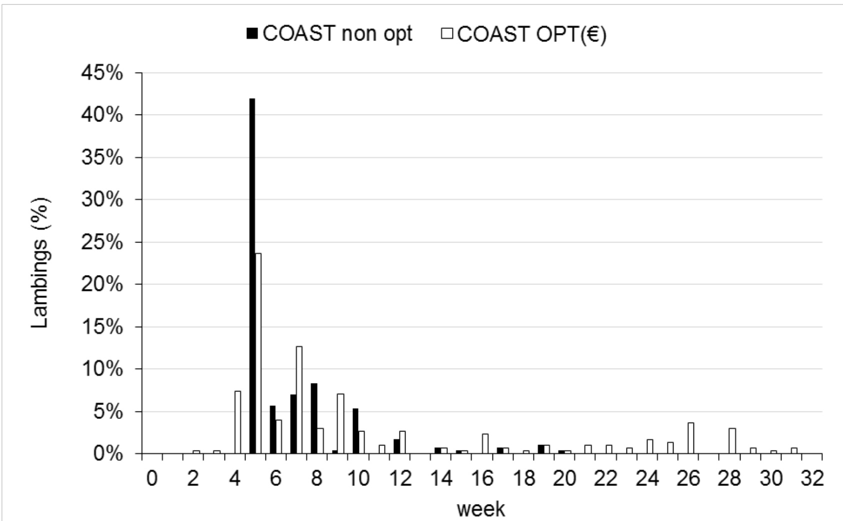
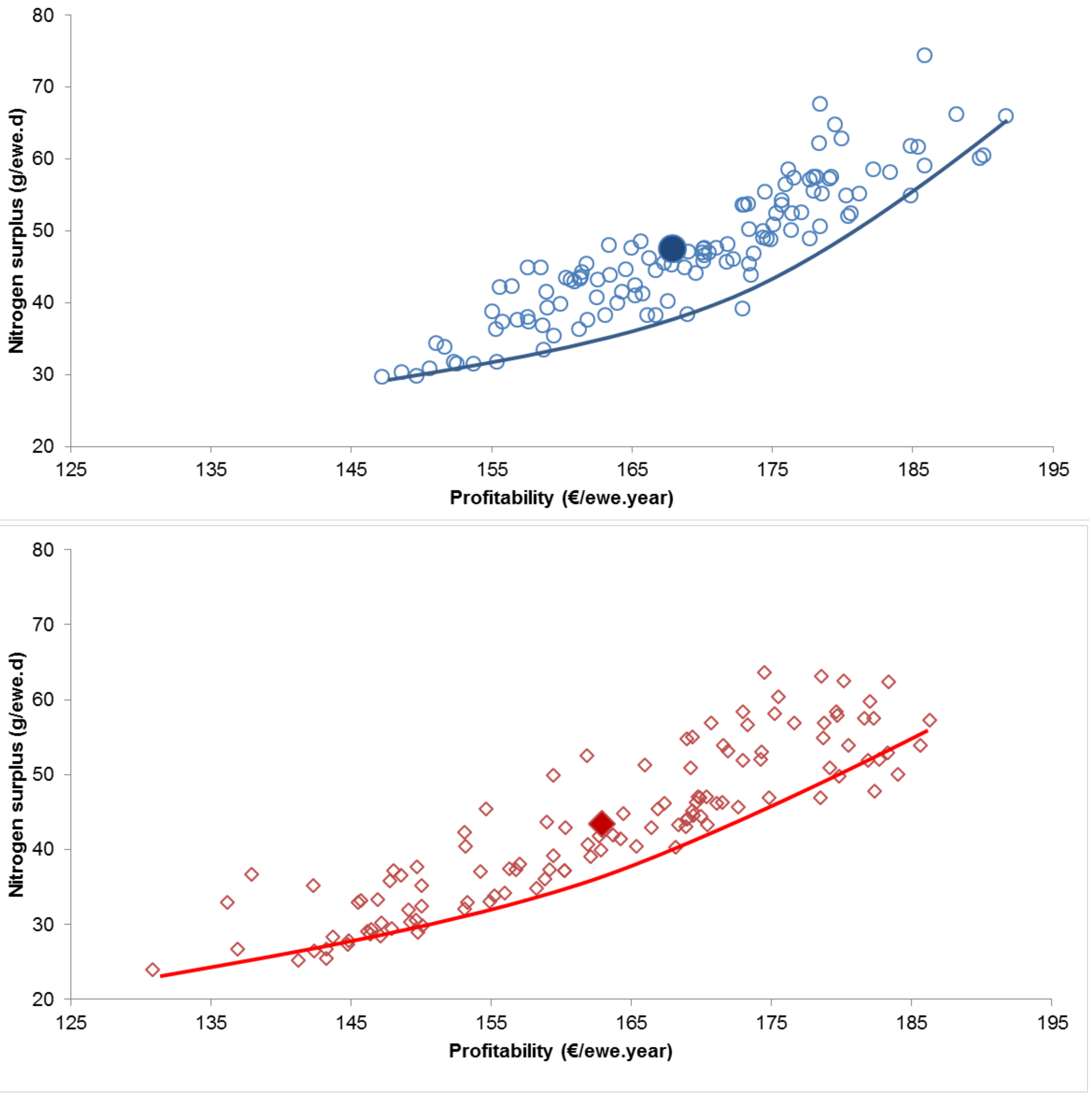
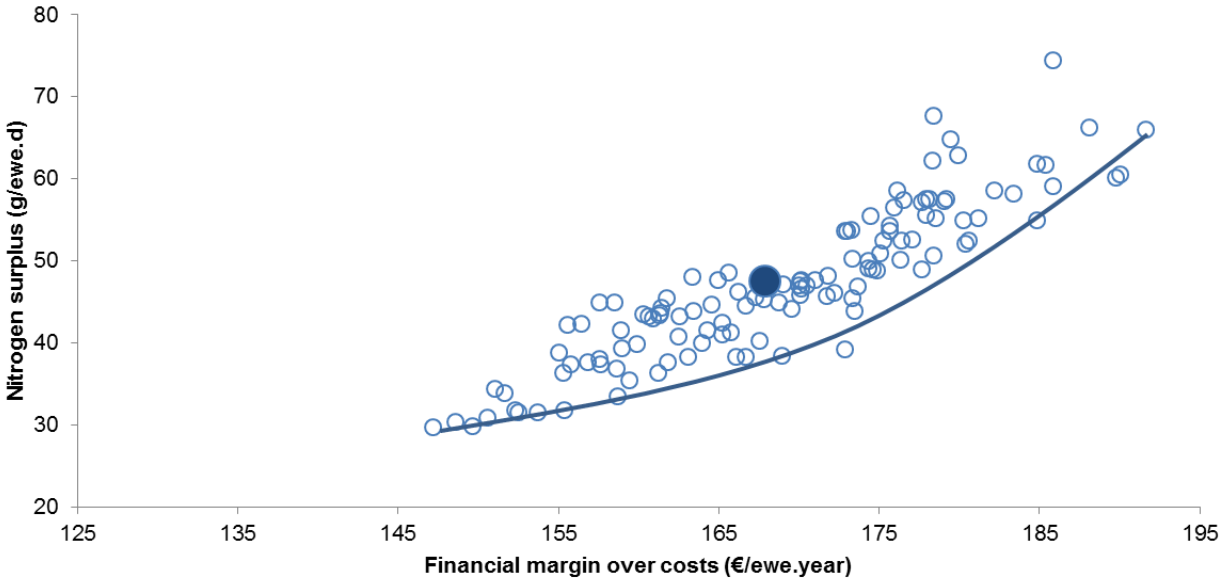


Figure 5. Optimal solutions obtained from the genetic algorithm in the COAST (○) and INLAND (◊) scenarios. Filled markers represent the mean solution in each scenario.




Nitrogen surplus (g/ewe.d)
Financial margin over costs (€/ewe.year)
20
30
40
50
60
70
80
125
135
145
155
165
175
185
195

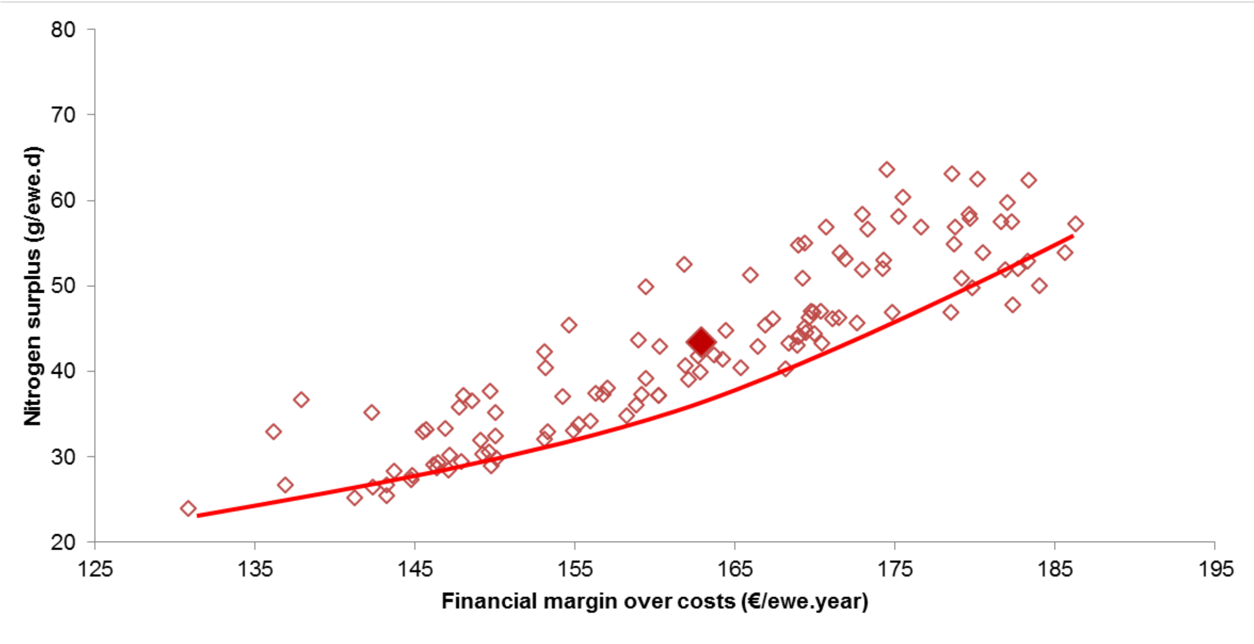
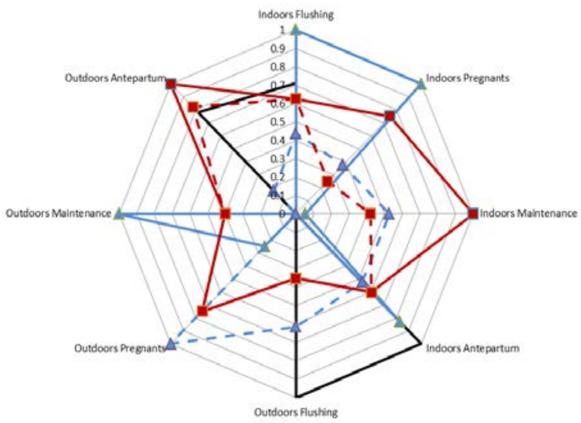
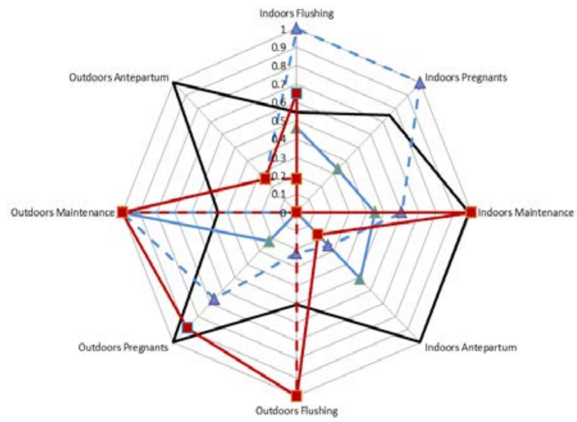

Nitrogen surplus (g/ewe.d)
Financial margin over costs (€/ewe.year)
20
30
40
50
60
70
80
125
135
145
155
165
175
185
195

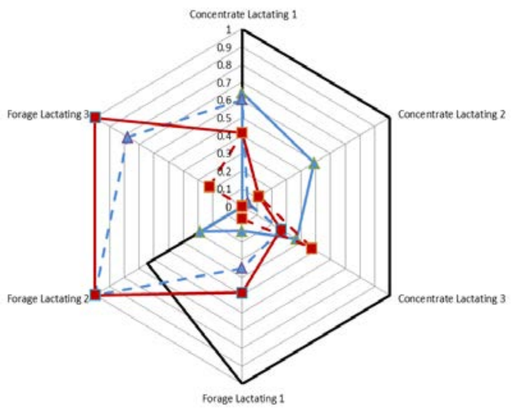
Figure 6. Optimal solutions obtained in COAST and INLAND farms for economic (€) and nitrogen surplus (N) objectives referred to the original values before optimisation (base scenario)



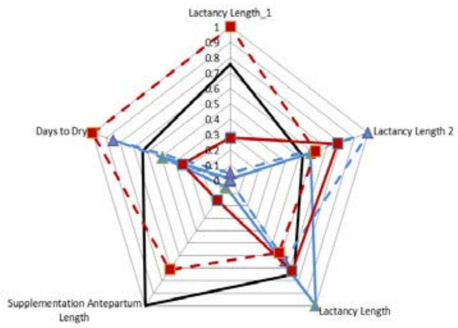
Concentrate inclusion (kg)



Forage inclusion (kg)



Forage and concentrate for lactating ewes (kg)



Length of feeding periods

BEFORE COAST OPT € COAST OPT N INLAND OPT N INLAND OPT €